Reconstruction of multi-shot diffusion-weighted MRI using deep learning

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INTRODUCTION

Background

- DW MRI has been widely used in clinical applications and neuroscience research
- A relaxed convex model has been proposed to do image reconstruction
- Convex optimization requires long reconstruction time

Previous Work

- Unrolled network with deep priors to accelerate convex optimization.
- A relaxed convex model with locally low-rank regularization for DW MRI reconstruction
- U-net for image classification

Why CNN can reconstruct MRI?

- Neural network can learn proximal operators
- MRI reconstruction by convolution in frequency domain
- Proximal operator of L1-regularization is similar to ReLU

Data acquisition

- Number of shots = 4
- The acquired data was first zero-filled to 256 x 256 and then normalized based on non-diffusion-weighted images.
- 1734 images used for training
- 858 images used for validation

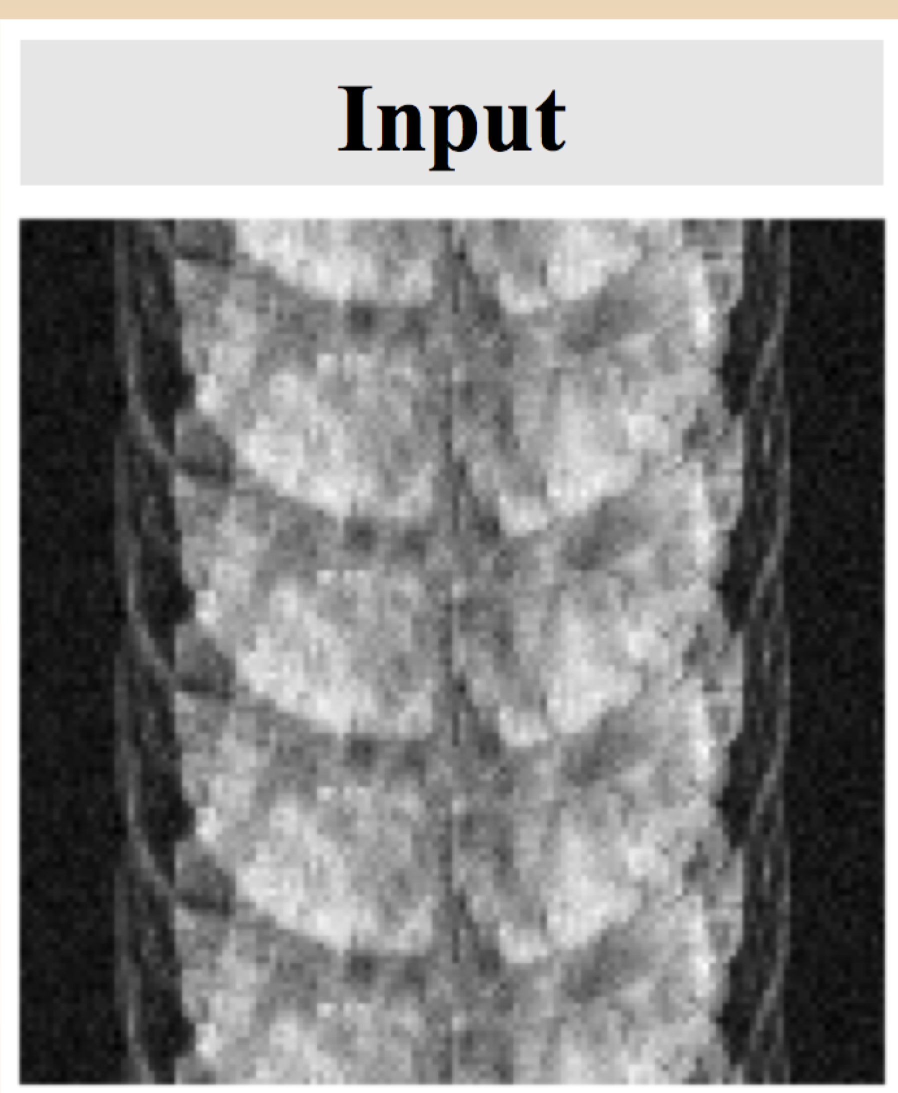

Figure 1. A typical input to network.

METHODS

1. Conventional convex optimization method

$$\min_x \underbrace{\|Ax - y\|_2^2}_{\text{data consistency}} + \underbrace{\lambda g(x)}_{\text{regularization}}$$

2. Unrolled Network

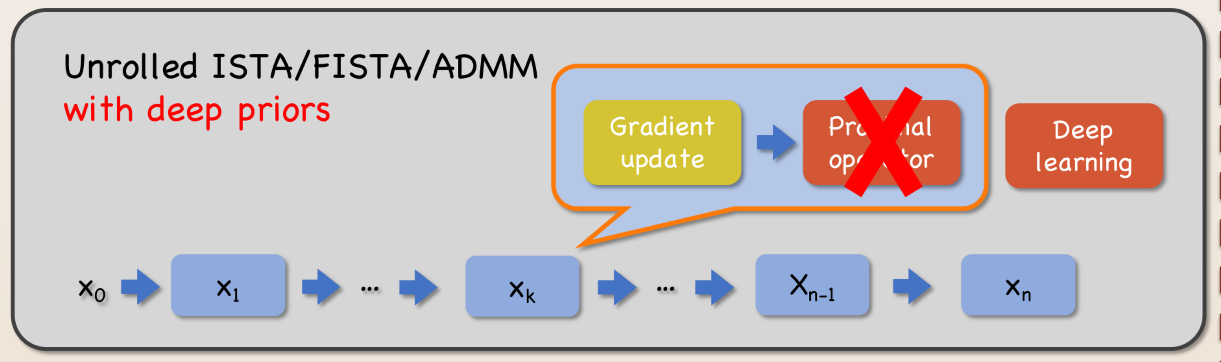

Figure 2. Schematic diagram of unrolled network with deep priors

- Replace the proximal operator in conventional optimization methods with a much more efficient function (U-Net)
- Let the data self-pick the efficient function to converge
- Network in different iterations can be quite different

3. U-Net

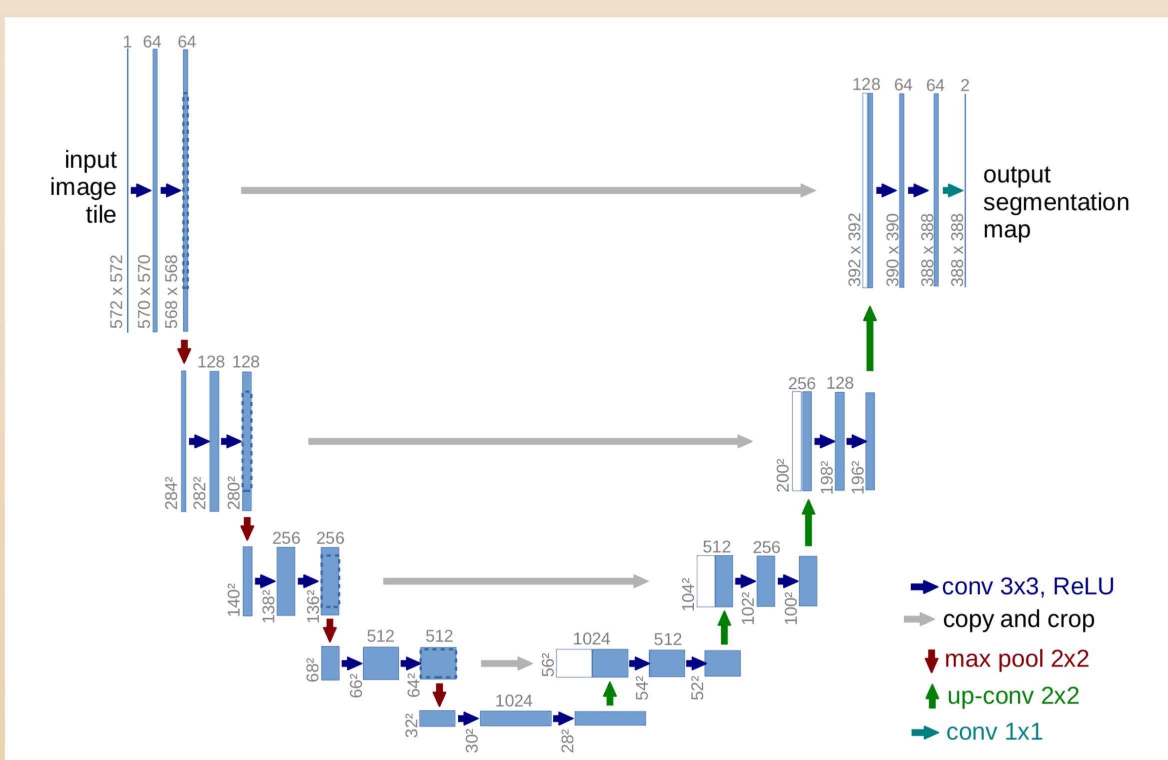

Figure 3. Schematic diagram of U-Net network

- Fancier version of ResNet and idea similar to FractalNet
- Kernels at different level capture features in different scalings
- Convolutions layers at top level focus more on local structures, while layers at bottom have a bigger version

4. k-i domain input for CNN

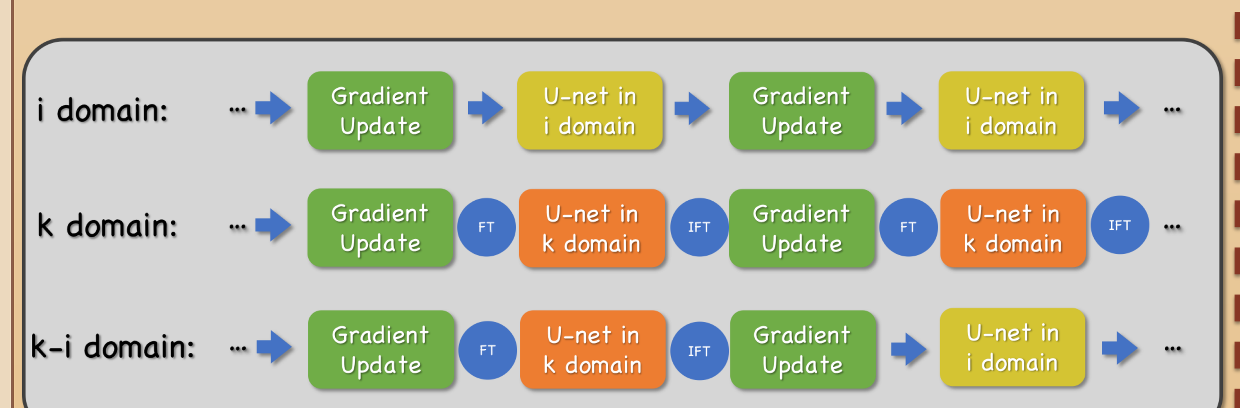

Figure 4. Schematic diagram of network structure with k and i domain input for CNN

- Alternatively use k domain or i domain data as the input for CNN network
- Reconstruction in k-space is more natural
- In image domain help remove structural artifacts

EXPERIMENTS

1. Different #iterations

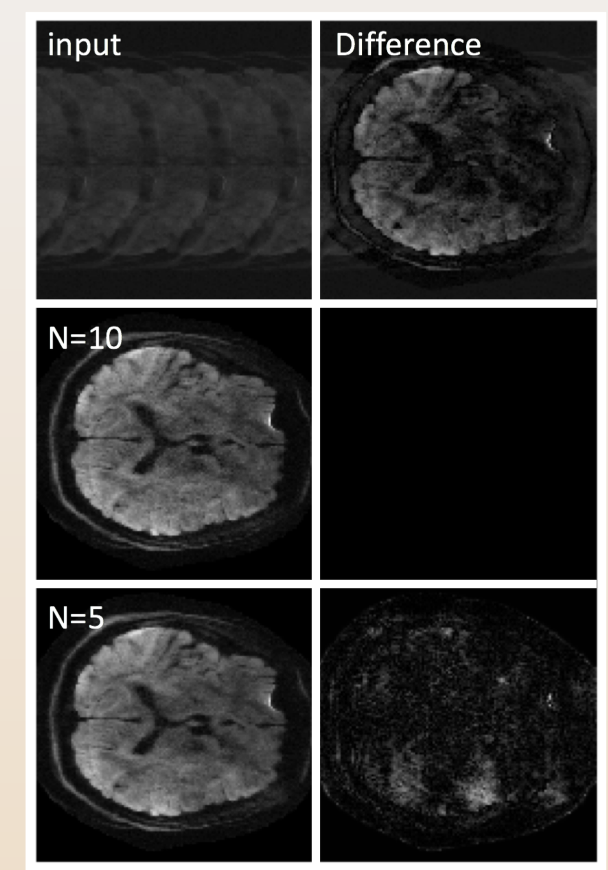

Figure 5. Representative output image for N=5 and N=10

- Perform experiment with N = 5, 8, 10, 15 for i-net
- Increasing N=5 to N=10 yields significantly better images
- Further increasing N=10 to N=15 does not improve the reconstructed image much
- 10%-15% of recon images still have noticeable artifacts even with N=15

2. Outputs from different networks

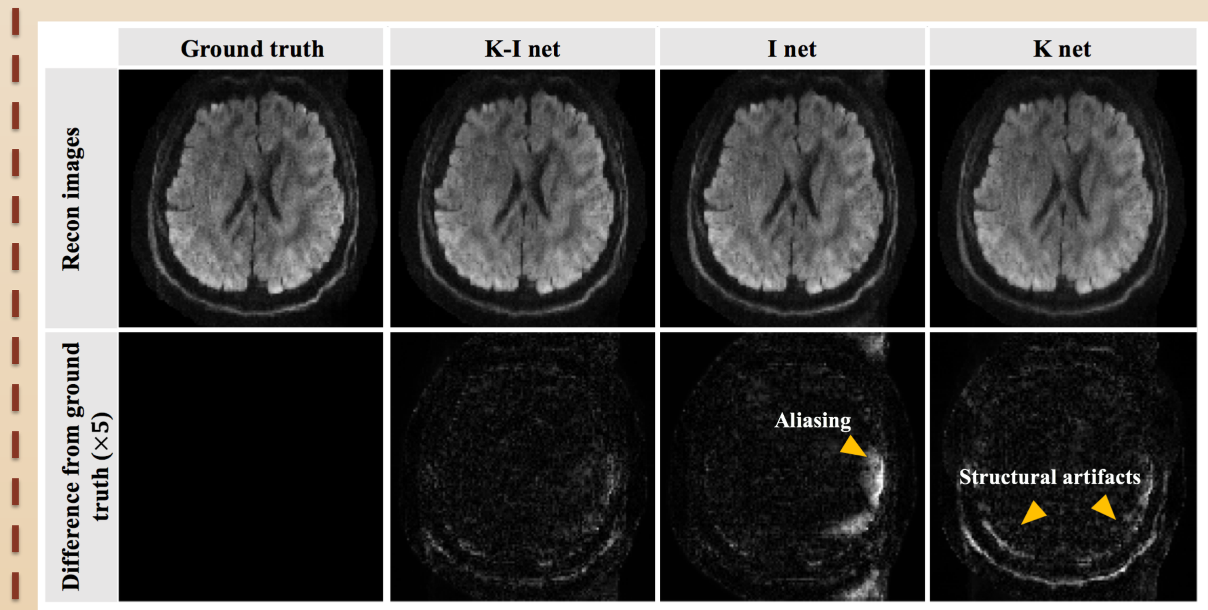

Figure 6. Representative reconstructed images from all three networks.
Second row shows the difference from ground truth(5X).

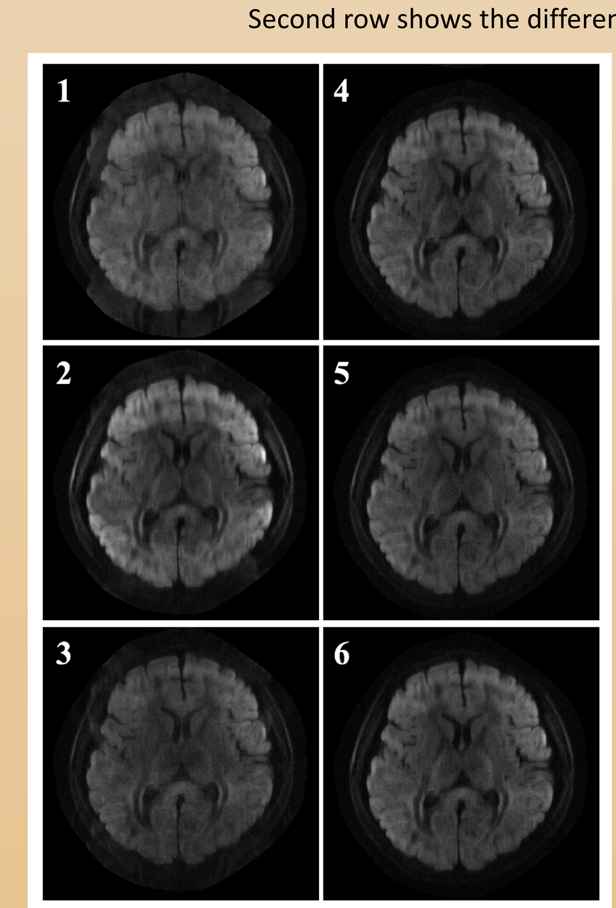

Figure 7. Visualize output image at each iteration (N=6)

- Setting input in image and frequency domain alternatively performs best
- For k-i net, significant improvements from N=4 to N=6
- Set N=6, reconstructed image at each iteration are shown on the left

3. Test results

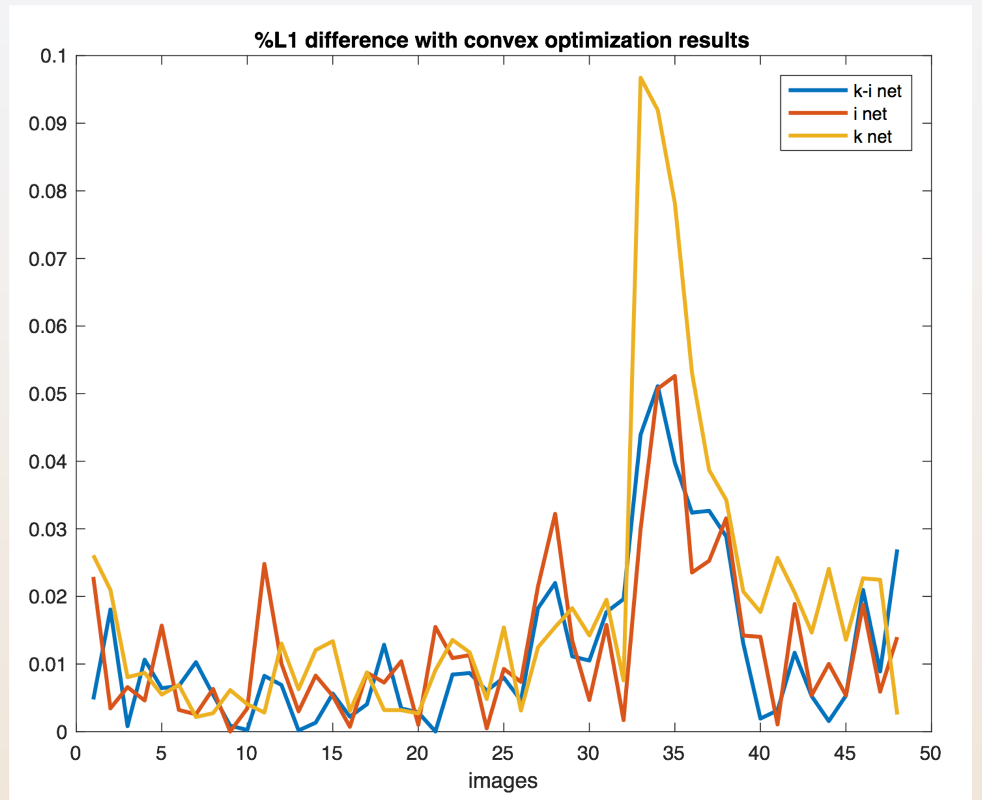

Figure 8. Percentage differences plot for 48 test images

CONCLUSIONS

In this work, we replaced the presumed LLR regularization term with a U-net to accelerate multi-shot DW MRI reconstruction. Our main contributions are as follows:

1. k-i net achieved best performance
2. reconstruction time from 1min down to 1s
3. average L1 difference ~1%

DISCUSSION & FUTURE WORK

- More data (data augmentation)
- Different network structures
- Different loss functions

REFERENCES

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